Anti-Cheating Prosumer Energy Exchange based on Indirect Reciprocity

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Abstract—**Equipped with renewable energy generators, prosumers produce, store and consume energy and become an important entity in smart grids. With time-variant power demands and generation capacities, prosumers can exchange energy via local power lines with less transmission loss than the long-distance power lines to the traditional power plants. In this paper, we develop a local power exchange game and address the cheating problem that seller prosumers actually supply insufficient energy instead of the promised amount in the trade. We apply the indirect reciprocity principle to build an anti-cheating local energy exchange system that maintains reputations for the prosumers according to their selling histories. By supplying less energy to the buyers who cheated in previous trades, this system motivates the autonomous prosumers to cooperate instead of cheating. Simulation results have shown that this strategy significantly reduces the number of cheating prosumers and improves the overall system utility. Compared with the direct reciprocity-based counterpart, this system reaches the desirable equilibrium much faster and requires less energy from the traditional energy plants.**

I. Introduction

With the proliferation of advanced power services and technologies, prosumers are the combination of power producers and consumers and become an important entity in smart grids [1]–[4]. As a household, industrial or commercial establishment equipped with batteries and various appliances such as refrigerators and air-conditioner, each prosumer can also generate power by utilizing renewable energy generators, e.g., solar panels and small wind turbines, as well as power elements such as electronic vehicles(EVs) and plug-in hybrid electric vehicles (PHEVs) [1], [2], [5], [6].

Due to the time-variant power demand and renewable power production that depends on the weather condition and the number of the energy generators, the energy surplus of a prosumer, either positive or negative, changes over time and is different from each other [7]. Prosumers exchange their surplus energies in a local electric market as a supplement to traditional power plants. With lower transmission costs due to the shorter transmission distance, the local power exchange reduces the energy bills from energy plants and the investment costs to upgrade the power equipments for the ever-increasing power demands [3].

Controlled by distributed individual households, prosumers have autonomy and control in the local energy trade. Seller prosumers have incentives to send less energy than promised in the trade to the buyers to increase their own utilities, if knowing that cheating does not incur punishment. Secure energy exchange in the local electric market has become an important issue in smart grids [8]. In this work, we aim to address the cheating problem for autonomous prosumers in the energy exchange.

Game theory is a powerful mathematical tool for the design and analysis of smart grids and networks [7], [9]–[17]. For instance, in a power system consisting of several renewable power generators with different properties, the energy quantities for the generators have been optimized in terms of the system operating costs and emissions in the cooperative game [13]. In [15], the risky and firm power contract offering was introduced for the wind power producers to trade risky power. In addition, a microgrid coalition algorithm has been proposed in [14] to match the buyer and seller to reduce the power distribution loss. The work in [17] analyzed the energy trading between two microgrids and provided a centralized solution to minimize the total cost.

Moreover, the trust/reciprocity methods are especially efficient to enhance user cooperation [18], [19]. Among them, the indirect reciprocity principle with the main idea "I help you and somebody else helps me" has shown its strength in large-scale networks to overcome the limitations of the direct reciprocity strategy [20]. The indirect reciprocity principle has been applied to stimulate node cooperation for the large-scale cognitive radio networks [19] and to suppress eavesdropping and packet dropping attacks in wireless networks [21], [22]. Inspired by these works, we apply this principle to counteract cheating in prosumer power exchange.

In this work, we present a prosumer power exchange game and propose an anti-cheating local energy exchange system based on the indirect reciprocity principle. Note that a seller prosumer in a trade is likely to have insufficient energy afterwards and becomes a buyer in another trade due to the time-variant renewable energy production and power demand. Therefore, by reducing the power supply to the buyer prosumers who once cheated as sellers and ensuring that the punishment loss exceeds the cheating gain, the local energy market suppresses the cheating motivation of rational prosumers.

The indirect reciprocity-based energy market utilizes a social norm and prosumer reputation updating process to punish the the cheating sellers and those who help the "bad" buyers with insufficient power supply. In this way, the system

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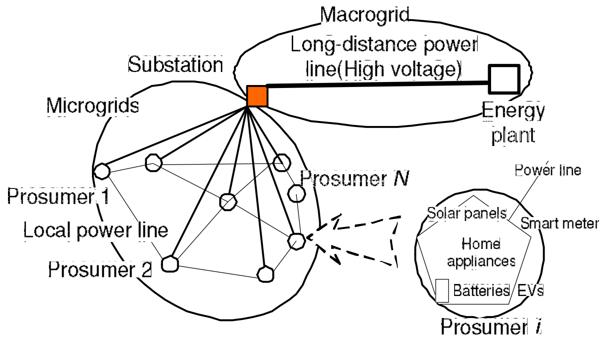


Fig. 1. A smart grid consisting of a traditional power plant, a substation and N prosumers.

N	Number of prosumers in the local market
L	Size of the action set
$a_{i,j}$	Action of a seller with reputation i to a buyer with reputation j
$\mathbf{a}^*$	Optimal action strategy
$\mathbf{Q}$	Social norm matrix
$\mathbf{C} = [C_i]_L$	Payoff vector (C_i: payoff of action i to the seller)
$\mathbf{G} = [G_i]_L$	Gain vector (G_i: payoff of action i to the buyer)
Φ	Reputation propagation matrix
ϵ	Reputation propagation accuracy
ρ	Percentage of buyer prosumers in the whole population
Λ	Forgetting factor vector
$U^{\mathbf{a}}_{i,j}$	Expected long-term utility function of strategy $\mathbf{a}$ as the seller (or buyer) reputation is i (or j)
p_l	Probability for a prosumer to have a reputation l

TABLE I
SUMMARY OF SYMBOLS AND NOTATIONS.

suppresses the incentive for rational prosumers to cheat and stimulates prosumer cooperation. We apply the Markov decision process to derive the stationary reputation distribution for the optimal trading strategy and use the Wright-Fisher model for the prosumer strategy spread to investigate the stable equilibrium in this game. Simulation results show that this system can suppress the cheating population in the energy exchange system very fast. Consequently, prosumers obtain more power from the neighborhood energy community and pay less to the power plants, which can decrease their fossil fuel consumptions and the overall carbon emissions.

The remainder of the paper is organized as follows. In Section II, we present the system model. Then we describe the indirect reciprocity-based local energy exchange in Section III and analyze its performance in Section IV. Simulation results are presented in Section V. A short conclusion is made in Section VI.

II. System Model

We consider a smart grid consisting of N autonomous prosumers that are connected with a traditional energy plant via a substation and long-distance power lines, as shown in Fig. 1. With time-variant energy demands and generation capabilities, prosumers also exchange their surplus energy in the local energy market via local power lines. The local energy trade is monitored by the smart meters and the substation in the microgrid.

For simplicity, the time under consideration is divided into slots as the unit of the energy exchange. We assume that in each time slot, ρ percent of the prosumers are buyers in the local energy market. Each buyer selects its seller prosumer according to its energy demand and trading policy, the local energy price and the energy generation capabilities of the neighboring prosumers. Assuming that both the seller and the buyer have agreement on the amount and price of the energy in the trade, we focus on the action of the seller, i.e., whether the seller indeed sends sufficient energy to the buyer as it has promised.

Due to the time-variant power demand and generation capability, a buyer in a trade at time k can become a seller to another prosumer in a later trade. Controlled by the household owners, the autonomous prosumers are assumed to be selfish and rational, i.e., they aim at maximizing their own expected utilities in the energy exchange.

In this system, the amount of energy in the trade are quantized into L levels. More specifically, a seller takes an action a from the action set $\mathbf{A} = \{1, \cdots, L\}$ and the amount of energy that the seller actually sent is $(\frac{(a-1)S}{L}, \frac{aS}{L}]$, where S is the amount of the energy promised by the seller in the trade. An action can be viewed as the ratio of the amount of energy that is actually sent over the claimed trade amount. It is clear that autonomous sellers have motivation to cheat in the trade with $a < L$, if they believe that cheating incurs no punishment.

The local energy market evaluates the selling actions of the prosumers and updates the seller reputations accordingly. Corresponding to the action set $\mathbf{A}$, we use a reputation set $\{1, \cdots, L\}$ with L levels of discrete reputations, where L is the best reputation and 1 is the worst. Let $a_{i,j}$ denote the action of a seller with reputation i to a buyer with reputation j and the L-by-L matrix $\mathbf{a}^* \triangleq [a^*_{i,j}]$ be the optimal strategy for the prosumers in the energy trade, where $a^*_{i,j}$ denotes the optimal action for a seller with reputation i towards a buyer with reputation j.

The utilities to the prosumers in the trade depend on the local energy prices, the claimed and the actual amounts of the energy exchanged among the prosumers, and the transmission losses over the local power lines. For simplicity, we assume a time-invariant utility function and define a payoff (or gain) vector $\mathbf{C} \triangleq [C_i]_{1\le i\le L}$ (or $\mathbf{G} \triangleq [G_i]_{1\le i\le L}$) as the immediate utility that the seller (or buyer) obtains, where C_i (or G_i) is the instant payoff to the seller (or buyer) with the selling action i.

Note that our proposed anti-cheating system is not restricted to the trade with fixed pricing or quantized energy amount. The indirect reciprocity principle can be extended to the time-variant pricing system, which exceeds the scope of this paper due to page limitation. For ease of reference, the commonly used notations are summarized in Table I.

III. Indirect reciprocity-based anti-cheating energy exchange for prosumers

We build a local energy market based on the indirect reciprocity principle to suppress cheating prosumers. By incorporating a social norm and reputation updating process, this market follows the principle "I help you and somebody else helps me" [20] in the energy trade. More specifically, the local energy market assigns a reputation value to each prosumer according to its selling history. On the other hand, sellers following the social norm choose their trading actions based on the reputations of the buyer prosumers and their own trading strategies.

This reciprocity-based system assigns two types of reputation to each prosumer: a scalar reputation and a vector reputation. Corresponding to the action set, the scalar reputation is an integer from 1 to L, where L is the highest (best) reputation while 1 is the lowest (worst). In the social norm, each seller takes action L by sending sufficient energy to the "good" buyer with reputation L and provides less power (i.e., $a < L$) if the buyer has a reputation less than L.

Besides the scalar reputation, we also introduce a vector reputation consisting of L elements to record more information on the prosumer's trade history, where the j-th element in the vector is the probability for the prosumer to have a scalar reputation j. Let $\mathbf{r}_l[k]$ denote the vector reputation of Prosumer l at time k, whose scalar reputation is actually the outcome of a random variable with probability mass function given by $\mathbf{r}_l[k]$.

The social norm of the local energy market is presented by the social norm matrix denoted as $\mathbf{Q} \triangleq [Q_{\alpha,j}]_{L\times L}$, where $Q_{\alpha,j}$ is the immediate scalar reputation assigned to the seller who takes action α to the buyer with reputation j. The social norm matrix is designed according to the desirable action strategy denoted with $\mathbf{a}^* \triangleq [a^*_{i,j}]$, which is a L-by-L matrix, where $a^*_{i,j}$ is the desirable action for a seller with reputation i to a buyer with reputation j.

Following a desirable prosumer strategy in the anti-cheating energy exchange, a seller sends the amount of energy according to the reputation of the buyer and the principle of indirect reciprocity. The seller has to punish the "bad" opponent prosumer according to the cheating history of the latter. For simplicity, one desirable action strategy is given by $a^*_{i,j} = j$ and thus

$$\mathbf{a}^* = \begin{bmatrix} 1 & 2 & 3 & \cdots & L \\ 1 & 2 & 3 & \cdots & L \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & 2 & 3 & \cdots & L \end{bmatrix}. \quad (1)$$

The seller takes action j towards a buyer with reputation j, and provides less energy to those deviating from $\mathbf{a}^*$.

To motivate prosumers to choose this strategy, the local energy market assigns the best reputation L to the sellers with $\mathbf{a}^*$. For example, the seller achieves reputation L if it sends sufficient energy to a good buyer with reputation L. Otherwise, the seller receives a lower reputation by either sending insufficient energy to the good buyer with reputation L or providing sufficient energy to those with lower reputations. According to this principle, we provide a social norm matrix as

$$\mathbf{Q} = [Q_{\alpha,j}]_{L,L} = \begin{bmatrix} L & L-1 & L-2 & \cdots & 1 \\ L-1 & L & L-1 & \cdots & 2 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & 2 & 3 & \cdots & L \end{bmatrix}. \quad (2)$$

For the case with $L = 3$, a seller prosumer obtains an instant new reputation 1 by taking action 3 to a buyer with a reputation 1 and earns a reputation 3 with the same action if the latter has the highest reputation.

As a concrete example of the reputation updating process, without loss of generality, we assume that Prosumer l with reputation i takes action $a_{i,j}$ to a buyer with reputation j at time k. According to Algorithm 1, the seller obtains a new vector reputation at time $k+1$ denoted with $\mathbf{r}_l[k+1]$ as follows,

$$\mathbf{r}_l[k+1] = \Phi(\lambda \mathbf{r}_l[k] + (1-\lambda)\mathbf{e}_{Q_{a_{i,j},j}}), \quad (3)$$

where the system parameter λ is the forgetting factor of a reputation, $Q_{a_{i,j},j}$ is the immediate scalar reputation given by (2), $\mathbf{e}_i = [0, \cdots, 1, 0, \cdots, 0]$ is the standard basis vector and Φ is the propagation matrix in the reputation broadcast process.

The new reputation $\mathbf{r}_l[k+1]$ is broadcasted to the other prosumers in the local energy market via a reputation broadcast channel. Let ϵ denote the probability for the reputation to be correctly broadcasted. For simplicity, we assume equal probability for a reputation to be detected with error and the probability for a seller prosumer to take reputation i as j is $(1-\epsilon)/(L-1)$, for given $1 \le j \ne i \le L$. Thus the propagation matrix in (3) is given by $\Phi = [\Phi_{i,j}]_{L,L}$, where the probability for an observer prosumer to take a new reputation i as j is $\Phi_{i,j} = \frac{1-\epsilon}{L-1}$, $j \ne i$, and $\Phi_{i,i} = \epsilon$.

Finally, we introduce a forgetting factor vector denoted with $\Lambda \triangleq [\Lambda_x]_{1\le x\le L}$ to discriminate the cheating degrees in the reputation updating process, where $\Lambda_x \in (0,1]$ is the forgetting factor for immediate reputation x. A larger Λ_x represents less impact of the current action in the long run. By setting $\Lambda_x < \Lambda_y$ for the instant reputation $x < y$, the local energy market punishes the cheater prosumers deviating from the desirable strategy for a longer time. As a system parameter, Λ is set by the energy market in advance. We investigate its impacts via simulation results in Section V. Similar to Eq. (3), the reputation updating process with differentiated forgetting factors can be written as

$$\mathbf{r}_l[k+1] = \Phi(\Lambda_{Q_{a_{i,j},j}} \mathbf{r}_l[k] + (1-\Lambda_{Q_{a_{i,j},j}})\mathbf{e}_{Q_{a_{i,j},j}}). \quad (4)$$

IV. Optimal Action & Stationary Reputation Distribution

The proposed energy exchange strategy provides incentives for prosumers to send sufficient energy to the "good" prosumers in the neighborhood energy community and suppress cheating in the local energy trade. In this section, we evaluate whether our desirable action strategy $\mathbf{a}^*$ in (1) dominates in the prosumer population and derive the corresponding stationary reputation distribution.

By applying the Markov Decision Process (MDP), we derive the stationary reputation distribution for the optimal strategy.

Algorithm 1 Reputation updating for prosumer l in the energy exchange process

Require: Current vector reputation of Prosumer l: $\mathbf{r}_l[k]$, action $a_{i,j}$, scalar reputation of the seller and buyer: i, j;

Calculate the immediate scalar reputation: $Q_{a_{i,j},j}$ by (2);

Check the forgetting factor: $\Lambda_{Q_{a_{i,j},j}}$;

Update the new vector reputation: $\Lambda_{Q_{a_{i,j},j}}\mathbf{r}_l[k] + (1 - \Lambda_{Q_{a_{i,j},j}})\mathbf{e}_{Q_{a_{i,j},j}}$;

Send the new vector to the prosumers in the area via the reputation broadcast channel.

Let $U^{\mathbf{a}}_{i,j}$ denote the expected long-term utility function of an action strategy $\mathbf{a}$ with seller reputation i and buyer reputation j. As the optimal strategy of a prosumer $\mathbf{a}^* \triangleq [a^*_{i,j}]$ maximizes $U^{\mathbf{a}}_{i,j}$, we have

$$a^*_{i,j} = \arg\max_{1\leq a\leq L} U^a_{i,j}. \tag{5}$$

Let $\mathbf{p}^* \triangleq [p^*_l]_{l=1,\cdots,L}$ denote the stationary reputation distribution of $\mathbf{a}^*$, where p^*_l is the time-invariant ratio of the prosumers with reputation l in the energy market. Thus the probability for a prosumer to meet a neighbor with reputation l in the next trade is p^*_l. Given long-term expected payoff $U^{\mathbf{a}}_{i,j}$, the expected utility to a seller with strategy $\mathbf{a}$ *since its next* trade is $\sum_{h=1}^{L}\sum_{l=1}^{L} r_{i,j}(h)p^*_l U_{k,l}$, where $r_{i,j}(h)$ is the probability for the seller to have a reputation h in its next trade and is equal to the h-th element of $r_{i,j}[k+1]$ in (4). Assuming equal probability for a prosumer in a trade to be a buyer or seller, we can write the expected long-term payoff of strategy $\mathbf{a}$ as

$$\begin{aligned} U^{\mathbf{a}}_{i,j} =& 0.5\left(C[a_{i,j}] + \sum_{k=1}^{L}\sum_{l=1}^{L} r_{i,j}(k)p^*_l U_{k,l}\right) \\ &+ 0.5\left(G[a^*_{j,i}] + \sum_{l=1}^{L} p^*_l U_{i,l}\right), \end{aligned} \tag{6}$$

where the first term corresponds to the case that the prosumer is a seller in this trade and the second represents the buyer. The difference between them is that the buyer in a trade keeps its reputation and obtains a payoff G while the seller has reputation updated and obtains a payoff C.

By Eq. (3), we use the time-invariant property of the stationary reputation distribution of $\mathbf{a}^*$ to obtain the following,

$$\mathbf{p}^* = \Phi\left(\lambda\mathbf{p}^* + (1-\lambda)\begin{bmatrix} \sum_{i=1}^{L}\sum_{l:Q_{a^*_{i,l},l}=1} p^*_i p^*_l \\ \cdots \\ \sum_{i=1}^{L}\sum_{l:Q_{a^*_{i,l},l}=L} p^*_i p^*_l \end{bmatrix}\right). \tag{7}$$

Using the modified gradient descent algorithm as presented in [19] on (5)-(7), we compute the stationary reputation distribution $\mathbf{p}^*$. For instance, we consider a case with $L = 2$ levels of energy quantization, where the payoff vector and the gain vector are $\mathbf{C} = [4, 2]$ and $\mathbf{G} = [-6, 8]$, respectively. According to Eq. (1) and (2), the desirable action strategy and the social norm matrix are simplified into

$$\mathbf{a}^*_{L=2} = \begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix}, \tag{8}$$

and

$$\mathbf{Q}_{L=2} = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}. \tag{9}$$

Based on the gradient descent algorithm, we see that the stable probability for $\mathbf{a}^*_{L=2}$ is $\mathbf{p}^* = [0.0285, 0.9715]^T$, i.e., prosumers with the desirable action strategy can obtain the best reputation with a probability 0.9715.

V. SIMULATION RESULTS

A. Evolutionarily Stable Strategy

Originally developed for social-biological science, the evolutionarily stable strategy (ESS) is used to evaluate whether an equilibrium in a game is stable [23]. More specifically, given a dominant strategy, the natural selection alone is sufficient to prevent alternative strategies from invading. To this end, the Wright-Fisher model [23] is widely used to investigate the action strategy spread resulting from natural selection.

According to the Wright-Fisher model, we perform simulations to evaluate the evolution of the prosumer population adopting our desirable strategy $\mathbf{a}^*$ and determine whether $\mathbf{a}^*$ in (1) is evolutionarily stable. More specifically, in a local energy market following this model, the probability for a seller to choose the strategy indexed with i at time $k+1$ is proportional to the expected utility to the population following strategy i at time k. Therefore, the probability for a seller to choose strategy i at time $k+1$ denoted with $p'_i[k+1]$ is given by

$$p'_i[k+1] = \frac{p'_i[k]U'_i[k]}{\sum_l p'_l[k]U'_l[k]}, \tag{10}$$

where $U'_l[k]$ is the average utility that the prosumers with strategy l obtain at time k.

B. Simulation results

We evaluate the evolutionarily stable property of the desirable strategy $\mathbf{a}^*$ in the energy exchange system, where the action spreading follows the Wright-Fisher model given by Eq. (10). As comparison, we also considered the direct reciprocity principle [20], whose main idea is "I help you because you help me", which clearly has better performance than those without any reciprocity/reputation mechanism.

Unless specified otherwise, we considered $N = 100$ prosumers and $\rho = 40\%$ of the prosumers bought energy in each time slot, with the forgetting factor $\lambda = 0.5$ and the reputation broadcast accuracy $\epsilon = 0.99$, where 70% of the prosumers follow $\mathbf{a}^*$ during the first time slot. We provide the percentage of the sellers that send insufficient energy, consisting of the cheating population and the prosumers that punish the cheaters, which can be viewed as the upper limit of the cheating ratio.

First, Fig. 2 presents simulation results for the case with $L = 2$, $\mathbf{C} = [4, 2]$, $\mathbf{G} = [-6, 8]$, $\mathbf{a}^*_{L=2}$ given by (8) and $\mathbf{Q}_{L=2}$ by (9). We see that the desirable strategy $\mathbf{a}^*_{L=2}$ is an evolutionarily stable strategy and this system suppresses the cheating population to less than 2% after 50 time slots. In addition, more than 90% of the prosumers choose our desirable action after 50 time slots in the indirect reciprocity system, in Fig. 2(b), and more than 98% of the prosumers have the highest reputation, in Fig. 2(c).

It is also shown in Fig. 2 that this system exceeds the direct reciprocity counterpart. For example, the "bad" prosumer population in this system quickly shrinks to a negligible level after 50 time slots, while the direct reciprocity-based system is much slower to achieve the same performance. The reason is that a prosumer is less likely to meet its previous seller again with exchanged roles in such a large-scale network and thus avoids the punishment resulting from cheating with a large chance.

We next consider the case that the system has a more accurate quantization level for the energy exchange with $L = 3$,

$$\mathbf{a}^*_{L=3} = \begin{bmatrix} 1 & 2 & 3 \\ 1 & 2 & 3 \\ 1 & 2 & 3 \end{bmatrix}, \tag{11}$$

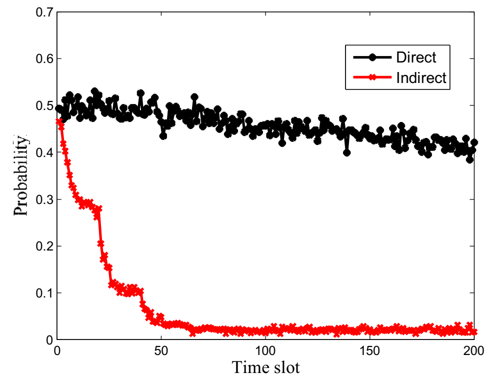
and

$$\mathbf{Q}_{L=3} = \begin{bmatrix} 3 & 2 & 1 \\ 2 & 3 & 2 \\ 1 & 2 & 3 \end{bmatrix}. \tag{12}$$

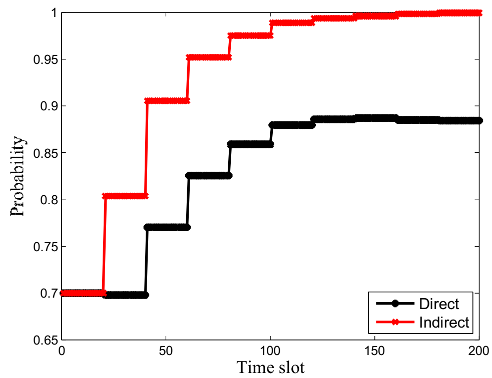
In the simulation, the payoff vector for the seller prosumers $\mathbf{C} = [4, 3, 2]$ and the gain vector for the buyer prosumers $\mathbf{G} = [-6, 1, 8]$. By comparing Fig. 2(c) and Fig. 3 (b), we see that a more accurate energy quantization (i.e., $L = 3$ vs. $L = 2$) improves the system performance and suppresses the cheating population much faster. Finally, as shown in Fig. 3, the overall system utility increases by replacing $\lambda = 0.5$ with $\Lambda = [0.2, 0.4, 0.8]$ and the discriminate forgetting factor for each action type prevents cheating more efficiently.

VI. Conclusion

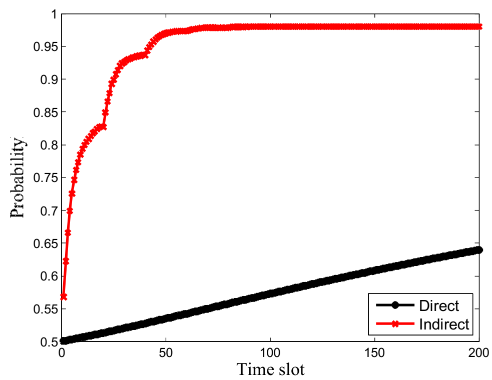
In this paper, we have proposed an indirect reciprocity-based local energy exchange system to suppress cheating of autonomous prosumers. The social norm and reputation updating process are established to punish the cheating prosumers with insufficient energy supply in later trades. We have provided the stationary reputation distribution of the optimal action strategy for prosumers in the local energy exchange according to the Markov decision process model. Simulation results show that our desirable strategy is an evolutionarily stable strategy and the system can suppress the cheating population very fast. In addition, by applying discriminate forgetting factors in the reputation updating, the system further increases the overall network utility and the speed to suppress cheating population.



(a) Percentage of the sellers providing insufficient energy.



(b) Percentage of the population using the desirable strategy, $\mathbf{a}^*$.



(c) Percentage of the prosumers with the best reputation (i.e., 2).

Fig. 2. The population evolution of the local energy exchange system consisting of $N = 100$ prosumers, with $L = 2$, and $\lambda = 0.5$.

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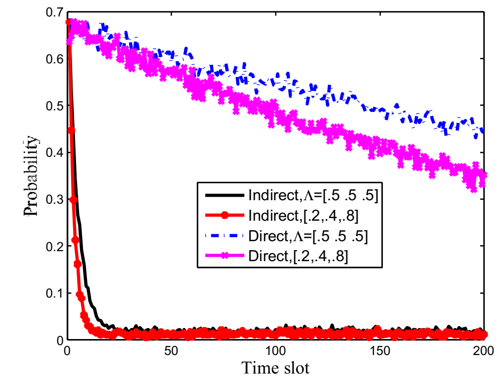
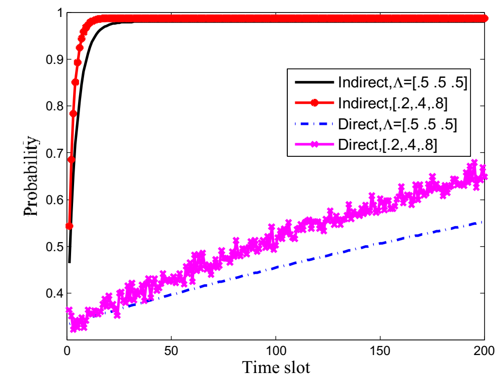
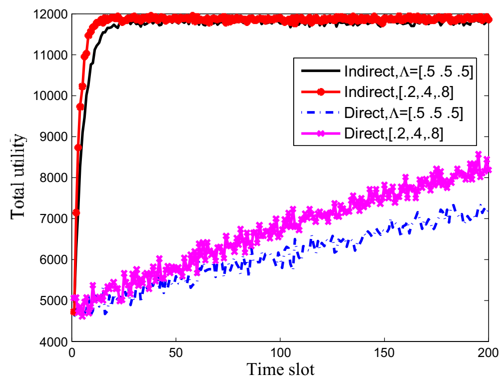


(a) Percentage of the sellers providing insufficient energy.



(b) Percentage of the prosumers with the best reputation (i.e., 3).



(c) Overall system utility

Fig. 3. The population evolution of the local energy exchange system consisting of $N = 100$ prosumers with $L = 3$ energy quantization levels, and different forgetting factor vector Λ.

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